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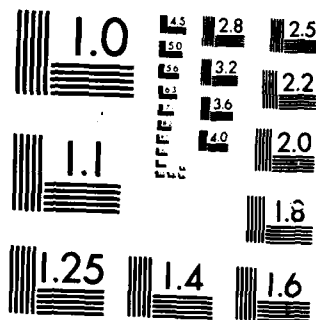
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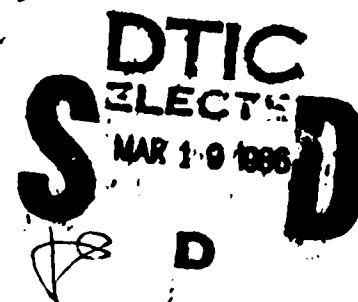
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by

Douglas M. Towne



BEHAVIORAL TECHNOLOGY LABORATORIES

Department of Psychology

University of Southern California

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The Engineering Psychology Group  
Office of Naval Research

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To obtain usable projections of total repair times, however, requires the estimation of the cognitive portion of fault diagnosis time as well. Unfortunately, the cognitive processes involved in fault diagnosis are complex, variable from one individual and circumstance to another, and almost entirely unsupported with research data quantifying their execution times. It becomes necessary, therefore, to explore the variations in cognitive times in relation to those characteristics of the diagnostic situation which can be quantified. Three such characteristics are analyzed in detail: 1) the number of tests required to isolate a fault, 2) the total manual time expended in fault diagnosis, and 3) the times of the individual tests in a diagnostic sequence.

Previous studies involving 87 technical participants, and three different systems under repair, obtained detailed data on 638 fault diagnosis episodes. Statistical analyses of these performance data reveal that the average cognitive time expended per fault was related to a significant degree to the three diagnostic characteristics. The most reliable predictor of actual cognitive time for a particular fault was obtained by computing an estimated cognitive time prior to each test based upon the manual time required to perform that test. The function relating cognitive time to the manual time of the following test action is a non-linear function derived from the experimental data. It indicates that cognitive time increases when the manual time of the following test increases, but quickly approaches an upper limit.

Since the PROFILE troubleshooting model produces good projections of the particular tests performed to accomplish diagnosis and repair, and their time durations, it can now also compute the estimated cognitive time preceding each test.

The sum of the projected cognitive and manual times correspond well with the experimentally observed total diagnosis and repair times. *See model*

Unclassified

## ABSTRACT

### Cognitive Workload in Fault Diagnosis

Prior research has produced a capability to project with reasonable accuracy the manual activities required to accomplish diagnosis and repair of particular faults within a specified system. When applied to a substantial sample of faults, the technique, termed PROFILE, provides an assessment of the manual workload expected to maintain the system.

To obtain usable projections of total repair times, however, requires the estimation of the cognitive portion of fault diagnosis time as well. Unfortunately, the cognitive processes involved in fault diagnosis are complex, variable from one individual and circumstance to another, and almost entirely unsupported with research data quantifying their execution times. It becomes necessary, therefore, to explore the variations in cognitive times in relation to those characteristics of the diagnostic situation which can be quantified. Three such characteristics are analyzed in detail: 1) the number of tests required to isolate a fault, 2) the total manual time expended in fault diagnosis, and 3) the times of the individual tests in a diagnostic sequence.

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## SECTION I. INTRODUCTION

Research conducted over the past four years has led to techniques for projecting the manual workload involved in performing corrective maintenance upon specific systems. The ultimate objective is to develop a process for projecting the distribution of total maintenance times (manual and cognitive components) for a system based upon its design specifications. Such a resource could support the design team in evaluating alternative design options, and it could be useful in procurement and logistic activities as well.

The approach is 'performance-based', i.e., the computed time to diagnose and correct a particular fault is synthesized from a detailed projection of the maintenance tasks required to accomplish isolation and repair of the fault. Doing this over a sample of faults in a system produces a distribution of maintenance times which characterize the maintainability of the design.

Earlier reports describe the development of the computer model of an expert troubleshooter (Towne, Johnson, and Corwin, 1982, 1983; Towne and Johnson, 1984). The model, called PROFILE, generates a sequence of manual actions to restore a system containing a specified failure. The manual operations which might be generated for a particular fault include testing, adjusting, disassembling, replacing, and reassembling. Each of the manual actions can be assigned a representative performance time, using traditional pre-determined time techniques (Karger & Bayha, 1966). The total manual times projected by PROFILE compare well with observed manual times.

Three important results of this performance-based approach are 1) it is sensitive to the ways in which the internal organization of the system affects the fault isolation process, 2) it is sensitive to the ways in which the physical structure of the system affects the necessary disassembly, testing, and repair tasks, and 3) it provides the ability to identify the source of maintainability problems, and to quantify their effects, all within the design phase of system development.

### Cognitive Aspects of Fault Diagnosis

The present goal is to generate representative projections of the cognitive workload in fault diagnosis, measured in time units. The power of the performance-based approach is essential to this endeavor, for it provides a reasonably accurate account of the diagnostic process associated with a particular failure.

Fault diagnosis is an activity which can present a fascinating and somewhat unique mental challenge. In the domain of everyday experience, troubleshooting seems to lie somewhere between

solving a crime and disarming a bomb. As the diagnostician initiates an investigation, he/she is presented a report that some undesirable events have occurred, resulting in an improperly operating physical system. The report may be fully reliable, partially incorrect, or completely erroneous. Further evidence may be gathered, but often the fault cannot be directly observed. The diagnostician usually has the option of proceeding to gather further evidence or of devoting time to further consideration of the available information.

To further complicate the situation, the actions of the diagnostician may increase the level of damage, they may present a danger to the investigator or to the system under repair, and sometimes they remedy the fault in ways that forever disguise its true nature. In the worst cases, there are multiple faults or faults which vary over time in ways which are exceedingly difficult to anticipate and fully understand.

The full inventory of cognitive functions involved in fault diagnosis entails an extremely wide range of mental activities. The diagnostician may have to recall recent events (symptoms obtained and test configurations employed) as well as events from the distant past (prior faults experienced, and their symptoms). The troubleshooter may have to recall or generate theories concerning how the particular system operates in various conditions. This may require reasoning about the possible cause of disperse symptom information, and about the specific tests which would discriminate those possibilities. Finally, the troubleshooter must accomplish some type of self-direction, ranging from conscious and explicit consideration of the available resources and constraints, to apparently ad-hoc decisions which the individual might have difficulty explaining.

While there have been considerable investigations into the nature of problem solving and planning processes, the focus has been primarily upon the types of functions and activities performed, and the characteristics of that mental performance, rather than the time required. Hamm (1985) has studied the ways in which experts shift their cognitive effort between 'intuitive and analytical cognition'; Rouse and Morris (1985) have considered the relationships between the domain and possible mental models held by human problem solvers; and Kahneman and Tversky (1979) have looked deeply into the ways human beings' decisions are influenced by risk. Perhaps the most pertinent previous research has been done by Hayes-Roth (1980) in studying the ways in which people plan complex activities, and the types of limitations encountered in estimating the time required to accomplish them.

Considerable work has been done measuring the time requirements to perform basic computation and perception functions. One comprehensive body of data developed by Quick, (Quick, Duncan, & Malcolm, 1962) provides detailed time data for such functions as visual inspection, reacting, computing, and reading.

Efforts to quantify cognitive activity in fault diagnosis face two imposing requirements: first, to make reasonably accurate projections of the cognitive processes involved in the diagnosis of a particular fault, and second, to quantify the time workload of those processes. These requirements are well beyond the current state of the art in cognitive science. Yet, there remains a clear and present need to arrive at assessments of cognitive time workload, to support the projection of total corrective maintenance times.

### Approach

The approach taken in this research was to search for reliable relationships between cognitive times occurring within experimentally observed corrective maintenance operations and the knowable characteristics of the associated task sequences. Projected cognitive times are then computed by applying these same relationships to PROFILE-generated troubleshooting sequences.

Four sections follow. Section II evaluates of the relationships between experimentally observed cognitive times and the nature of the diagnostic functions which were performed. The intent of this section is to present the findings, both positive and negative, which heavily influenced the search for a generalized approach to projecting cognitive time in troubleshooting.

Section III explores the relationships between the actual cognitive time expenditures and characteristics of the PROFILE projections of those diagnostic activities. The variables analyzed here are 1) number of PROFILE tests to isolate a fault, 2) total PROFILE manual time to isolate a fault, and 3) the times of the individual tests projected by PROFILE.

Section IV explores cognitive complexity in fault diagnosis, while Section V summarizes the findings of this research and discusses implications for future research.

## SECTION II. COGNITIVE TIME WORKLOAD IN FAULT DIAGNOSIS

While we may not have a clear idea what decisions are made in an environment as complex as fault diagnosis, it may be possible to quantify the significant factors which affect decision time by analyzing data from actual diagnostic tasks in terms of the characteristics of those tasks.

The cognitive time data used for this work were collected in studies conducted over the last four years. The primary purpose of these earlier studies was to obtain samples of representative diagnostic performance for use in deriving theories of diagnostic performance and in testing the PROFILE model as it evolved. Three basic studies were conducted, involving a total of 87 technicians, three different types of failed system, and 30 different faults, as shown below.

Study No.	Technician Participants	No. Faults	Diagnostic Episodes	Failed System
1	48	8	384	video simulation of microcomputer system
2	29	6	174	graphic simulation of network diagram
3	5	8	40	infrared (IR) transmitter/receiver, design A
	2	8	40	infrared (IR) transmitter/receiver, design B
Total	87	30	638	

Table 1. The Studies of Diagnosis Performance

In these studies, each technician diagnosed and 'repaired' each of the faults. In study one the performance of the tests, adjustments, and replacements selected by the technicians were displayed on a color video screen, in real time; in study two the test results were displayed on a graphics computer screen. In study three the participants performed all the troubleshooting work on real equipment, except for the replacements, which were done by an experimenter at the request of the technician. The order of presentation of faults to individual technicians was fully counterbalanced. Full details of the three systems and the study conditions are given in Towne and Johnson, 1984.

In all, detailed data for 638 fault isolation and repair episodes were obtained, each consisting of the following information:

- the sequence of tests, adjustments, and replacements performed
- the manual time expended performing each test
- the time period between each manual action, termed *inter-step cognitive time*.

The total cognitive time for a problem, by an individual technician, is the sum of the inter-step cognitive times for that individual's diagnosis procedure. The average cognitive time for a particular problem is the simple mean of the cognitive times for the individual participants on that problem.

According to the definition given above, cognitive time is that time during which no manual activity is being performed. It is recognized that cognitive activities also can occur during the performance of manual actions. These could range from monitoring the performance of the manual actions in progress to planning future testing, or reasoning about results already obtained. For the purpose of projecting total maintenance time, however, it is most convenient to classify work as 'manual' when observable work is being performed, and 'cognitive' when no manual actions are in progress. The PROFILE model and its associated manual time data address the time expenditures during the portions defined as manual, even if some cognitive activities occur during these periods.

### System-level Results

Appendix A presents the experimentally observed time data for the three systems studied, accumulated by technician; appendix B presents the results accumulated by problem. The two questions of concern here are whether there are well-ordered relationships among cognitive variables within a particular system, and whether there are relationships that seem to hold across systems.

Table 2 lists correlations for three pairs of variables, for each of the three systems studied. The data analyzed here are the individual problem solutions, thus for example the sample size for system one is 384 (forty-eight technicians, eight problems per technician).

Variable Pair		SYSTEM		
		1 n=384	2 n=174	3 n=80
cognitive time to solution	versus number of steps to solution	0.67	0.67	0.75
cognitive time to solution	versus manual time to solution	0.61	0.64	0.71
cognitive time to solution	versus cognitive time per step	0.80	0.69	0.65

Table 2. Correlations at the Systems Level

The correlations given in table 2 are all significant. Since the PROFILE model can be used to estimate the number of steps to solution and the manual time to solution, these initially appear to be promising indicators of cognitive time workload. The major concern then becomes whether the quantitative relationships are consistent across system designs. Section III presents the results of predicting cognitive time in this manner.

The significant correlations within systems are both interesting and intuitively reasonable. Diagnostic sequences requiring more testing steps or higher cognitive time per step would naturally tend to be higher in total cognitive time. Furthermore, solutions which require higher manual involvement, either as a result of increased numbers of tests or the necessity to perform more lengthy operations, would seem to also involve increased cognitive activity.

The low correlation between cognitive time per step and number of steps is more difficult to understand. We might imagine that when a diagnostic routine requires more steps to solution the cognitive time per step would also be higher, in general, as the problem is more difficult. Alternatively, we might expect a subject-effect, either that technicians requiring more tests to find faults also are slower in conducting the cognitive actions, or that those individuals who devote less time to non-manual processes suffer by having to perform more tests.

Detailed examination of individual solution sequences reveals the possibility of several types of effects. In some cases technicians appear to be 'fishing', by performing many tests, but devoting little time to considering the results or to selecting the next test. Perhaps these individuals are searching for some particular indication, and are ignoring the more subtle information content of the tests. In these cases a high number of tests are observed with a low cognitive workload per test. There are other cases when the cognitive times per test are unusually high when the number of tests to isolation is high. These may be cases where the symptom information is difficult to interpret, where the selection of a useful test is difficult, or where significant strategic alternatives are available to be considered. They may also be cases in which the individual's cognitive style is different from those who do more testing and less evaluation and planning.

Compounded upon these partially offsetting effects are possible problem effects. Some faults may lead troubleshooters into extremely complex areas of the system, thereby necessitating a high cognitive involvement per test, while others may be resolved via a sequence of easily performed and interpreted tests. Clearly the detailed performance data cannot be easily interpreted unless subject effects and problem effects are considered individually. The next section looks deeper into the variations in cognitive time attributable to individual technicians, while the subsequent section investigates problem effects.

### Individual Differences in Cognitive Time Expenditures

Do better diagnosticians dwell longer on the meaning of tests than less effective technicians, or do they spend less time, possibly as a result of better understanding or innate reasoning power? Does an increased investment in reasoning time pay off in reduced manual time and reduced total fault isolation time? To explore these questions the individual technicians are ranked according to the amount of cognitive time each one expended solving the problems, and grouped into three categories of near-equal size.

Figure 1 presents the manual and cognitive times expended by each group, on the average, for the IR system (system 3). While the cognitive time per problem varied from 268 seconds to 503 seconds, from the low cognitive group to the high cognitive group, the manual time expended per problem was virtually identical across the three groups. This independence between manual time and cognitive time, at the individual technician level, was equally true for the other two systems studied. An analysis of variance confirms the lack of a significant effect of subject-group upon manual time ( $F=0.0529$ ,  $p=0.9485$ )

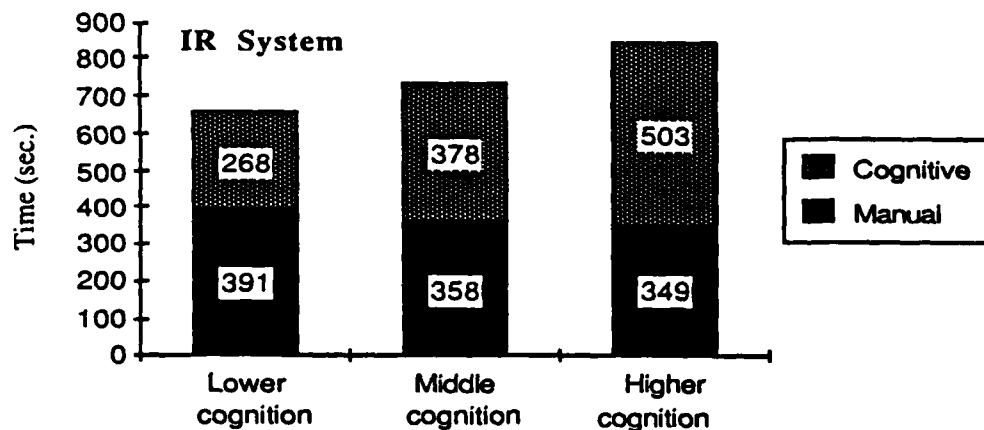


Figure 1. Cognitive and Manual Times, by Cognitive Group - IR System  
(Technicians Grouped by Cognitive Time per Problem)

Variations in number of tests and cognitive time per test may be examined using these same groups. Figure 2 presents the results for the IR System, and indicates that 1) the number of tests performed did not differ significantly by cognitive group, and 2) the cognitive time per test increased significantly by cognitive group. This indicates that the reason for the increased cognitive time per problem, for the higher-cognition group, was higher cognitive time spent per test, rather than increased numbers of tests.

Appendix C provides a summary of these data, for the three cognitive groups in each study.

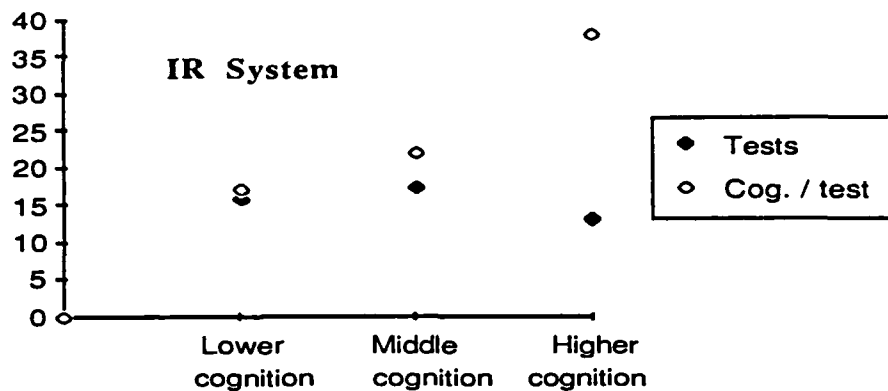


Figure 2. Number of Tests and Cognitive Time per Test - IR System  
(Technicians Grouped by Cognitive Time Per Problem)

When individuals are grouped by their total isolation and repair time, including both cognitive and manual effort, the better maintainers are found to expend less time in both manual and cognitive activity in all three systems studied, with the one exception that the middle-total group in the IR System study performed slightly less manual work than the lower-total group. Figure 3 presents the results for the IR system.

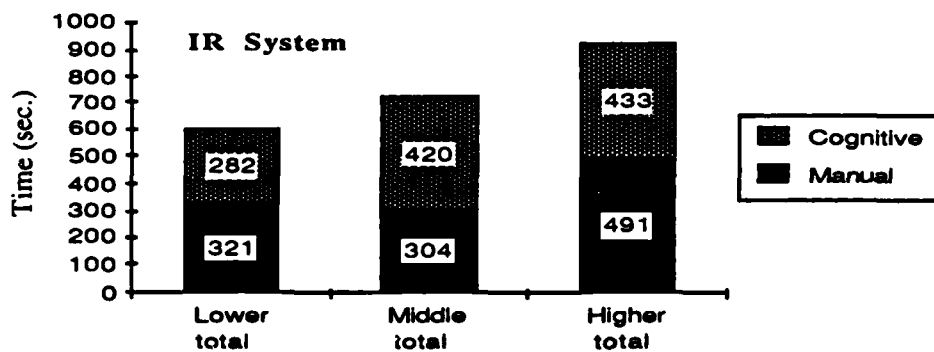


Figure 3. Cognitive and Manual Times, by Cognitive Group - IR System  
(Technicians Grouped by Total Time per Problem)

The reduced manual time expended by the better troubleshooters appears to be a result of better test selection, rather than a faster workspace, for the pace of performing manual tasks was controlled in two of the three studies (in studies one and two all manual operations selected by the subjects were shown being performed via color video tape).

As before, individuals spending more total time were found to devote more cognitive time per test, although the effect was less consistent. These individuals also tended to perform slightly

more tests than their more effective counterparts. Appendix C provides the data for the three studies, grouped by total fault diagnosis time.

### Problem Effects

Possibly the best opportunity for understanding more about the ways system design can affect cognitive workload is to explore ways in which diagnostic performance varied across individual problems. A central question concerns the source of higher cognitive time requirements for some problems over others. Does increased cognitive workload result from greater numbers of tests, higher cognitive time per test, or both?

Figure 4 displays the average cognitive time per problem for each of the sixteen faults inserted into the IR transmitter/receiver system. The problems are presented in order of increasing cognitive time. Figure 5 displays the average number of tests and the average cognitive time per test, for each problem, shown in the same order as in Figure 4. For this system, higher cognitive workload resulted from both increased numbers of tests and increased cognitive time per test.

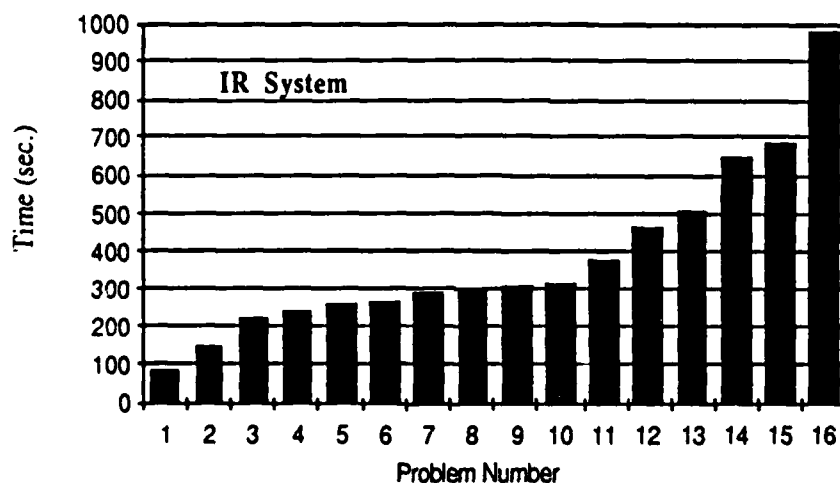


Figure 4. Cognitive Times for 16 IR System Problems  
(ranked in order of increasing cognitive time)

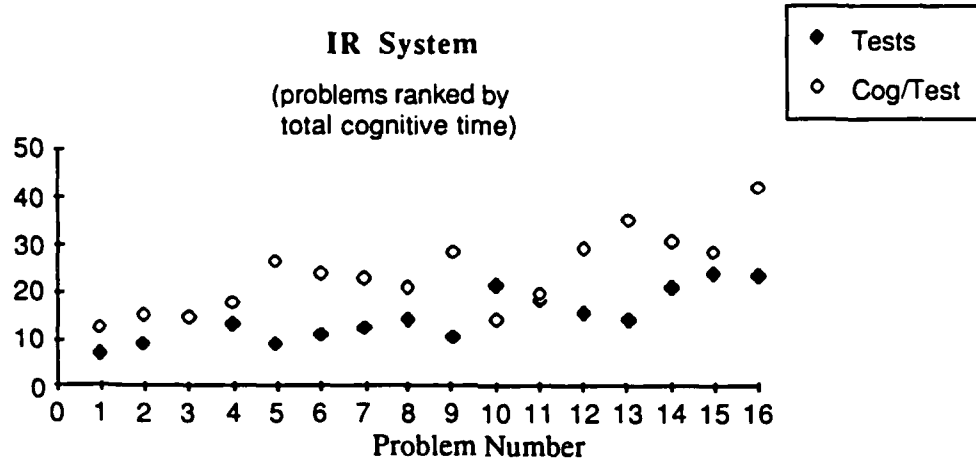


Figure 5. Number of Tests and Cognitive Time per Test, by Problem (IR System).

For the other two systems studied, increased cognitive time on particular faults was a result of increased cognitive time per step only; the more time-consuming problems did not involve more tests being performed. It is important to note, however, that the cognitive times per problem varied only by a factor of approximately two, for these two systems, while the longest cognitive time is ten times the shortest, for the IR System. In general, the results obtained for the IR system are believed to be the more typical, as the experimental conditions were extremely realistic for that study.

### SECTION III.

#### PROJECTING COGNITIVE TIME WORKLOAD IN FAULT DIAGNOSIS

The approach used by PROFILE to project manual times to perform operations is one of synthesis; it predicts the sequence of manual tasks which will be performed to accomplish some goal, and then sums the times of each of the manual elements. The results correspond well with observed times because a body of time data exists for assessing the duration of manual actions.

A similar approach to predicting cognitive times would require the ability to predict the cognitive activities performed, and the times required to accomplish those mental functions. While this might be accomplished with some success for extremely simple mental tasks, such as some types of choice tasks, we have neither the ability to predict the cognitive content of a complex diagnosis activity nor the means for quantifying the time requirements of those mental processes.

The approach taken, therefore, was to attempt to find characteristics of the projected diagnostic sequence which account for as much variation in cognitive time across problems as possible. More specifically, three variables were explored for the extent to which they relate to cognitive time; 1) number of tests performed, 2) total manual time in the diagnosis sequence, and 3) sum of manual times of the individual tests in the sequence. In all three cases, PROFILE is used to predict the value of the variable of interest.

Appendix D presents a detailed listing of the PROFILE projections, upon which the cognitive time projections are based. The projections are summarized in Appendix E. The projections of cognitive time shown in these appendices are based upon estimates of inter-step cognitive times, as discussed later in this section.

The annotation used in the remainder of this section employs three basic variables; C which is actual cognitive time, T which is actual number of tests, and M which is the actual manual time. Estimates of these are indicated as primed variables; for example T' and M' are PROFILE-generated estimates of the number of tests required to resolve a fault and the manual testing time involved, respectively. Values obtained as a result of curve-fitting are indicated with ^; for example an estimate of C, using a curve fit to experimental data is  $\hat{C}$ .

#### Number of Tests

Figures 4 and 5 showed that, for the IR System, actual cognitive time per problem increases as actual number of tests performed increases. The cognitive times for all thirty problems are shown in Figure 6 versus the number of tests in the PROFILE solutions to the problems. The

number of tests in some PROFILE solutions are non-integers, since PROFILE employs a sampling process when it must resort to sequential replacements. This technique yields a set of reasonable solutions to those problems in which multiple components are replaced in an arbitrary sequence.

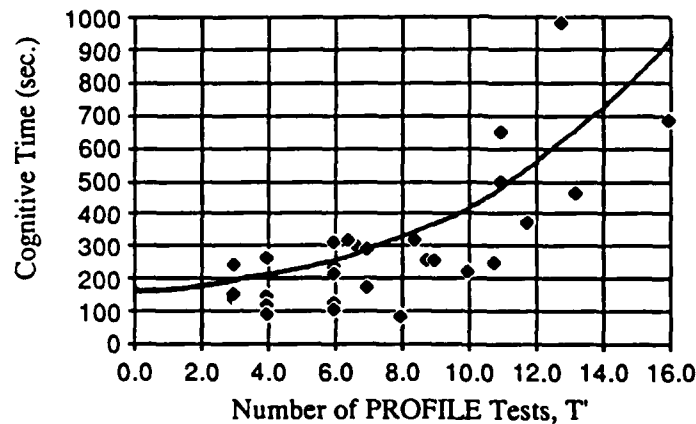


Figure 6. Cognitive Time per Problem versus Number of PROFILE Tests

The empirically derived curve fit to these data is

$$\hat{C} = 177 + T^{2.4}$$

where  $\hat{C}$  is the calculated cognitive time for the problem, in seconds

$T$  is the number of tests projected by PROFILE to diagnose and fix the fault

Figure 7 illustrates the success with which this exponential function corresponds to the cognitive times for the thirty problems studied ( $R=0.78$ ;  $F=44.42$ ,  $p=0.001$ ).

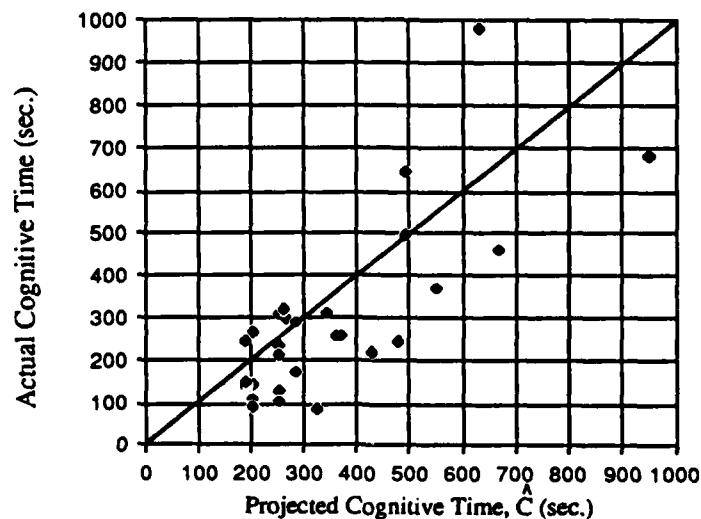


Figure 7. Projected Cognitive Times per Problem, based on Number of PROFILE Tests

While the computed times correspond rather well with the actual times, the generality of the function between number of tests and cognitive time is unknown. If a system design imposes tests averaging ten minutes, for example, the cognitive time per test is expected to be much greater, and the projected cognitive time, according to the function given above would be low. If the mean test times for some design are very short, the opposite is true. For these reasons manual time is now considered, as an indicator of cognitive time.

### Manual Time Per Problem

The second analysis attempts to relate cognitive time to the total manual time computed by PROFILE to diagnose and resolve each fault. As shown in Figure 8, the relationship between actual cognitive time per problem and projected manual time is not reliable when the problems from all three systems are pooled (linear regression yields  $R=0.46$ ).

When the data are analyzed by system, the times are found to vary closely (and linearly) with total manual time, but the parameters of those functions are significantly different for each of the three systems. Cognitive time and manual time seem strongly related, but not in a manner which is general across domains. The basic difficulty is that the cognitive time for a ten-minute problem will differ significantly if those ten minutes arose from one or two tests, as opposed to many tests.

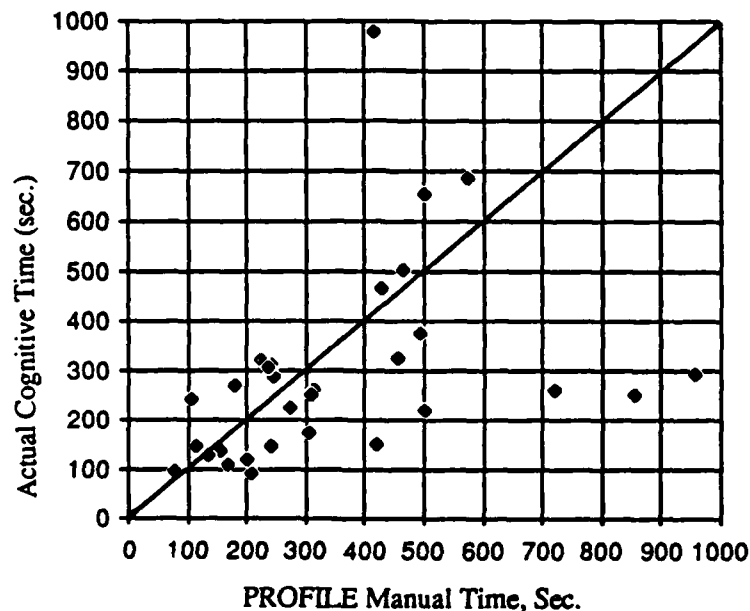


Figure 8. Manual and Cognitive Times, by Problem

The following section investigates cognitive times within a fault diagnosis sequence, with the objective of developing a relationship which is sensitive to numbers of tests performed and to the manual workload of the individual tests involved.

### Manual Times of Individual Tests

The third approach uses a form of synthesis, in which the cognitive time for a problem is computed as the sum of the cognitive times projected to occur between each two tests, i.e., the interstep cognitive times. The objective is to derive a function which is sensitive to the manner in which manual time was expended, i.e., whether it arises from performing many brief tests or a few long tests. Unfortunately, we currently have no way to know what part of an observed inter-step cognitive time was devoted to assessing the results of the previous test, and what part was spent planning the next action. Very specialized studies would be required to obtain these time portions individually. All efforts to discover a multi-variate relationship between inter-step cognitive time and characteristics of both the preceding and following test were entirely unsuccessful.

One relatively stable relationship, however, was obtained for the three systems studied which relates inter-step cognitive time to the manual time of the following test. Figure 9 presents the average cognitive time preceding a test versus the manual time of the test. Each data point shown represents the average of all the inter-step cognitive times preceding manual tests of a particular duration, across all three systems studied (Appendix F presents the data values; the data were accumulated for each diagnostic episode until the first replacement was made). The first data point shown, for example, indicates that the mean cognitive time preceding a manual test of five seconds in duration was 9.7 seconds (N=86).

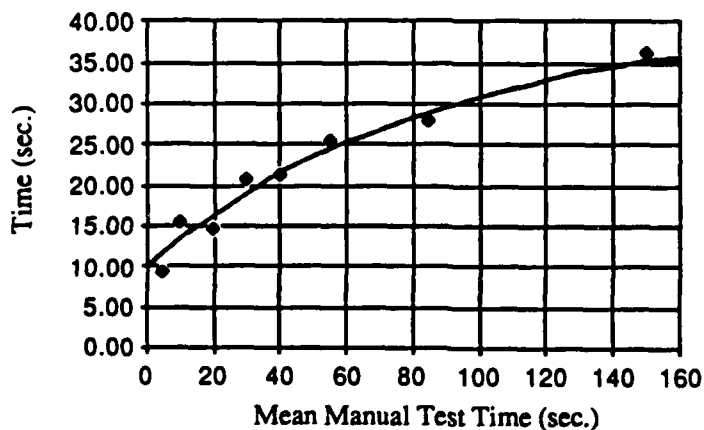


Figure 9. Average Inter-step Cognitive Times

The curve fit to these data is

$$\hat{IC} = 10 + M'^{0.65}$$

where  $\hat{IC}$  is the projected inter-step cognitive time

$M'$  is the manual time of the following test, as projected by PROFILE

This relationship appears most promising as a means for assessing cognitive workload, for it appears to be generally correct for each of the individual systems studied as well. The only difference found when interstep cognitive times were computed by system was the Y-intercept, representing a constant per test, which was 14 seconds for the IR system, and 8 seconds for the other two systems combined. More importantly, the exponent of 0.65 provided a good fit to the results summarized by individual system.

Appendix D lists the PROFILE diagnosis sequences for each of the thirty faults studied. This listing also displays the inter-step cognitive times computed according to the function  $10 + M'^{0.65}$ .

### Computing Total Cognitive Times

The total estimated cognitive time to diagnose a fault is simply the sum of the  $\hat{IC}$  computed at each test;  $\hat{C} = \sum \hat{IC}$ .

Figure 10 displays the total projected cognitive times for the thirty problems in the three systems plotted against the actual average cognitive time per problem, across all subjects. As seen in this figure, the PROFILE projections tend to be significantly low for three problems involving high actual cognitive time.

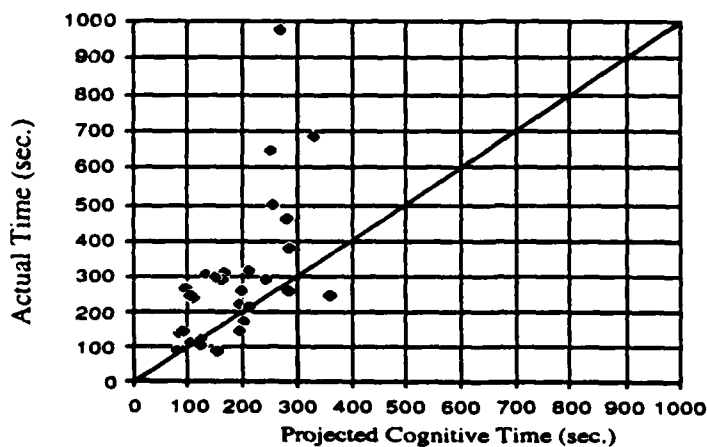


Figure 10. Projected Cognitive Times per Problem, based on PROFILE  
Projections of Inter-step Cognitive Time

These faults (IR faults 1, 6, and 9), are also ones which required significantly more steps to solution by PROFILE. When number of PROFILE steps is included in the projection function, the following achieves the best fit to the data:

$$\hat{C} = \sum \hat{IC} - 59 + T^{2.4}$$

where  $\hat{C}$  is the projected cognitive time to diagnose a fault

$\hat{IC}$  is the inter-step cognitive time prior to each PROFILE test, computed as  $10 + M^{0.65}$

T is the number of PROFILE tests

Figure 11 displays the projected cognitive times for the thirty problems using this function, versus the actual cognitive times ( $R = 0.755$ ;  $F=37.082$ ).

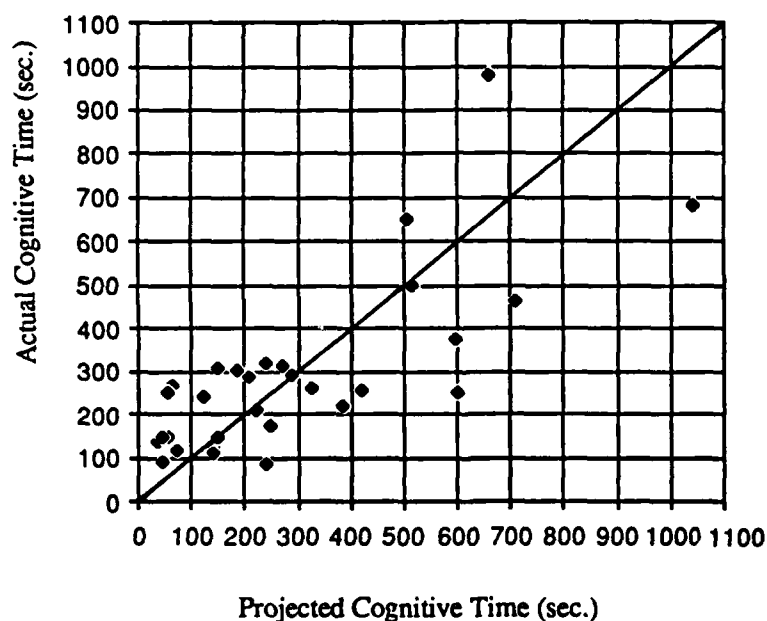


Figure 11. Projected Cognitive Time based on Inter-step Cognitive Time and Number of Tests

### Projections of Total Maintenance Time

Figure 12 displays the projections of total maintenance time versus the actual total times, averaged across all subjects and problems in the three systems. The projections are the sum of the cognitive times shown in figure 11 and Appendix E, and the manual times projected by PROFILE also shown in Appendix E.

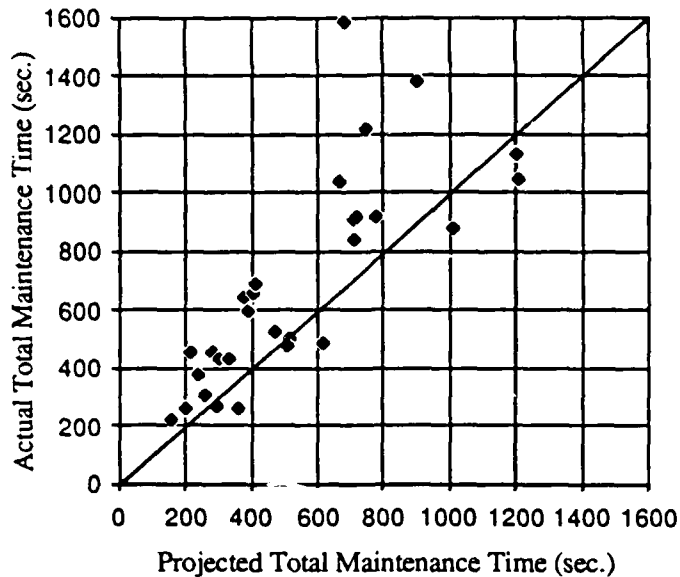


Figure 12. Projected and Actual Total Maintenance Times

As seen from Figures 7, 10, and 12, one particular fault caused the technicians considerably more difficulty than would be predicted by the characteristics of PROFILE diagnosis sequences. This fault is problem six, IC 46, a 2-input AND gate failed in the IR System, as shown in the schematic diagram in Appendix G. This component happens to be one of several in a feedback circuit. When it fails, the circuit runs continuously, rather than halting periodically to reset counters. To the troubleshooter, the observable signals may appear generally normal. If the abnormality is detected, the symptom does not assist in identifying the faulty component. Since the output of IC 46 is an extremely brief reset pulse, there is no effective way to detect it with standard test equipment. Thus, in this design the troubleshooter must ultimately resort to sequential replacement until the fault is resolved.

The functions developed here to reflect cognitive time workload only partially recognize such technical difficulties posed by the system design. While the existence of a feedback loop was not explicitly specified to PROFILE, the troubleshooting model did encounter the same difficulty in isolating the fault as the actual technicians did, i.e., it resorted to sequential replacement when no effective test could be found to discriminate the true source of the abnormality. The fact that the particular signal being tested was difficult to interpret, however, was not considered in the function for cognitive time.

Ultimately, it may be possible to develop a more comprehensive projection technique which is sensitive to a wider range of conditions. The following section addresses this objective.

## SECTION IV. COGNITIVE COMPLEXITY IN FAULT DIAGNOSIS

The variables used in the previous section to project cognitive time are indirect measures of cognitive workload. They vary with actual cognitive time variations because they reflect the difficulty PROFILE has in diagnosing a problem. Within a particular system design, faults which require more PROFILE tests or lengthier manual testing are faults which either do not produce many abnormal symptoms, and are therefore difficult to detect, or whose symptoms are difficult to discriminate from those of other faults, or both. This is true because the PROFILE model attempts to resolve problems in the most effective manner possible, and resorts to lengthy or numerous tests only when forced to by the system design and the nature of the fault.

The projections of cognitive time workload should stand up well across electronic systems, for the function relating inter-step cognitive time to manual time of the following test appears to be relatively stable in somewhat different electronic environments. There is no evidence, however, concerning its applicability in domains where the options, penalties, and distributions of task times are widely different from those encountered in electronic maintenance.

The following sections discuss an analysis of cognitive workload which may allow assessing cognitive workload in a wider range of domains in the future.

### Types of Cognitive Complexity in Fault Diagnosis

The sources of cognitive difficulty in diagnosis are numerous. It is useful, therefore, to somewhat partition the possibilities. Cognitive workload is viewed as being affected by three main influences: 1) the complexity of the system architecture concerned with fulfilling the missions of the system, termed *operational complexity*, 2) the complexity of the process required to diagnose faults in the system, called *process complexity*, and 3) the complexity of the resource-allocation and planning environment, termed *executive complexity*.

These three types of characteristics mutually influence many of same specific diagnostic functions. For example, we propose that cognitive time devoted to selecting a test is affected by the complexity of the particular diagnostic sequence in progress, by the complexity of the system under repair, and by the issues confronting the troubleshooter at the planning and resource allocation level. How these factors combine to impact cognitive workload is not at all clear.

#### Operational Complexity

Operational complexity relates to the ease of understanding the functions of the system under

repair, in both normal and failed conditions. This should not be confused with such measures as testability, which reflect the ease with which system functions can be monitored. Operational complexity is a characteristic of the way the system is designed to accomplish its mission functions, and it excludes consideration of design features intended to facilitate maintenance (such features are considered in the next section). While operational complexity can heavily influence ease of maintenance, the designer may have relatively little opportunity to simplify the hardware which accomplishes the primary missions of the system. High operational complexity may increase the difficulty of devising and interpreting tests which assist in isolating faults.

While operational complexity is affected by the number of physical components in the system, the cognitive difficulty of working in the domain of a particular design may be much more related to the organization of the components, and the nature of the functions which those components perform.

Currently, it is very difficult to compare the complexity of the internal architecture of two system designs. This is largely so because 1) the forms of representing those designs typically contain immense amounts of implicit information, and 2) the elements and interconnections shown may be of differing degrees of internal complexity. A block diagram of one system, for example, could scarcely be compared to that of another design, for the degree of detail represented within the blocks is a matter of arbitrary choice. Even two detailed schematic diagrams would be exceedingly difficult to compare, for the components and signals could be of vastly different levels of complexity. Furthermore, an assessment of cognitive workload would be very difficult to develop based upon a schematic diagram, for these involve a wide inventory of specific components.

A more feasible approach may be to develop a more generalized form of representation which involves highly common, generic functions. In such a representation all outputs and inputs would either be of comparable complexity, or they would carry some notation expressing the extent to which they are formed by combining simpler signals. The problem here is not one of developing an exotic representation form; a block diagram approach may be adequate. The problem is in representing a system in a consistent form such that measures could be computed which reflect the complexity of the system's operation. Experimentation could then be devoted to measuring how cognitive workload varies with this computed value.

The function of some idealized systems currently can be inferred from block-diagram representations if the following are true:

1. all outputs are time-invariant, and single-valued
2. a failure in any block causes all of its outputs to be abnormal
3. any abnormal input to a block causes all of its outputs to be abnormal

Much of the research of troubleshooting behavior, including our study two, has used systems which conform to these conditions. These conditions are rarely true for real-world systems, however, although portions of some analog systems approach this level of simplicity. More typically, some output lines can carry a multitude of possible values depending upon the configuration of the system, failures in some blocks only impair some of their outputs, and some abnormal inputs impact only some of the outputs of the blocks they drive. In the most complicated cases, outputs vary over time, outputs become inputs to feedback loops, and outputs are complex combinations of multiple signals.

Representations of complex systems can often be developed which meet conditions two and three above, by successively decomposing complex system elements into sub-structures. Of course this decomposition yields a representation involving many more blocks and explicit interconnections than were evident in the original block diagram or schematic diagram, but in this form the system behavior is fully specified in terms of comparable generic functions and signals. Other types of system complexity resist simplification or representation in a standardized manner. If a system design requires complex signal paths and complex signal forms, there is a limited opportunity for representing this in more elementary forms.

If a standardized representational format can be attained, then systems of widely differing architecture could be compared by computing the numbers of signals and signal conversions, as suggested by Leuba (1962) or Wohl (1980). Moreover, experimentation could be undertaken to explore how cognitive workload varies in relation to computed complexity values.

It is important to reiterate that operational complexity is expected to *influence* diagnostic workload, but that it does not fully determine the diagnostic effort. Since, by definition, operational complexity addresses the technical environment in which diagnosis occurs, it should be combined in some manner with the implications of diagnostic difficulty related to the particular diagnostic sequence. A technique for assessing the complexity of the diagnostic process is presented below.

### Process Complexity

Process complexity relates to the cognitive workload encountered in conducting diagnostic performance. More specifically, it pertains to the functions of maintaining the information gained by previous tests, in a particular fault diagnosis sequence, and of selecting future actions which will increase that information in manageable ways. Unlike operational complexity, which reflects the general technical environment in which all fault diagnosis in that system occurs, process complexity is a direct function of the particular actions performed, and hence of the fault being isolated. Thus

some faults do not require diagnostic sequences which involve significant complexity, while others force the troubleshooter to delve deeply into the more difficult sections of the system.

In general, the system designer can reduce process complexity in two ways, 1) provide tests which reflect the operation of system functions in convenient and powerful ways, and 2) reduce the requirement for the maintainer to develop ad-hoc diagnostic procedures. Thus a system with high operational complexity could be made to exhibit low process complexity by providing built-in tests which are easy to conduct and interpret, or highly proceduralized diagnostic approaches. When these resources fail to identify a fault, however, the maintainer of such a system must then generate a testing sequence in an environment of high operational complexity

The difficulty of attaining a cognitive objective, like identifying the source of a fault, is determined by the particular method employed to attain the objective. When measuring the manual difficulty of attaining some objective, like tuning an automobile engine, we must first specify how the work is to be done. Inexperienced mechanics may pursue methods which cause the work to be very difficult, while more experienced individuals may be able to avoid some of the difficulty. Thus manual difficulty is not a quality which is inherent to an objective but is inherent to the means for attaining the objective. Similarly, cognitive difficulty can only be defined in terms of a particular sequence of cognitive activities performed.

As with manual performance, there are great variations among individuals in the cognitive activities they perform to attain identical objectives. Which of all these possible approaches, then, should be used as the basis for evaluating the cognitive difficulty of a particular task? One feasible approach is to base this evaluation upon the decisions made by an expert troubleshooter. Thus if we know that an expert will resolve a particular fault in a particular manner, we can retrospectively analyze the character of the task at each stage. Since we have a model of an expert troubleshooter in PROFILE, we can use its diagnostic strategies as the source of this evaluation.

The complexity at each stage of a testing sequence is determined by evaluating the suspicions which exist as a result of all previous tests. If, for example, the previous tests in a sequence indicate that the fault must be in Unit A of a system, and cannot be in Unit B, then the suspicion state at this stage is extremely simple. Furthermore, the complexity at this stage is considered to be independent of the internal complexity of each of the units. In succeeding tests the complexity of the separate units may have to be confronted, but at this particular stage it can be avoided by the diagnostician.

If, on the other hand, previous test results point to certain sub-sections within Unit A, and some parts of Unit B, then the suspicion state is more complicated.

**Example.** Suppose the system under consideration is represented as shown in Figure 13. In this example there are two modules (I and II), five boards (A,B,C,D,E), and twelve Replaceable Units (RU's).

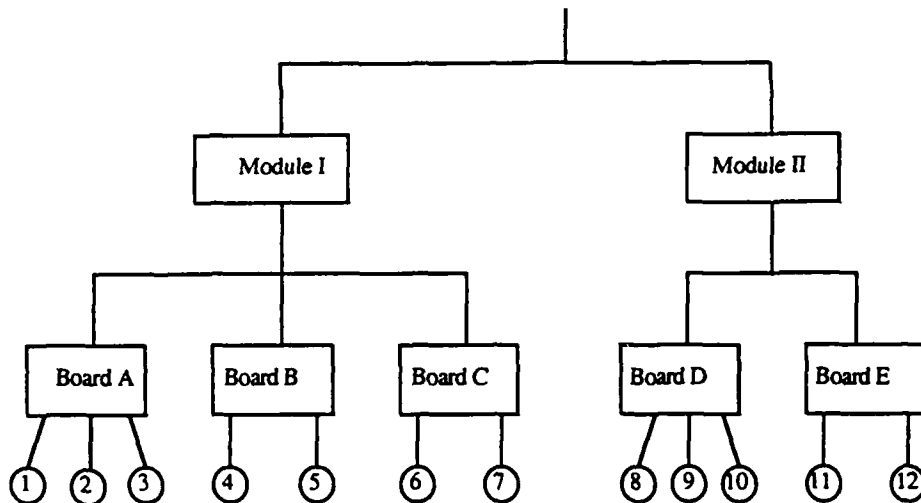


Figure 13. A Sample System Hierarchy

At any stage of diagnosis we may attach a probability to each RU, representing the relative suspicion we hold that the fault is in that RU. Initially, these probabilities are computed from our estimates of the relative failure rates of the RU's. As testing progresses we can revise the probabilities according to the evidence which each test produces. The exact value of these suspicion levels is relatively unimportant. For the purpose of identifying what sections of a system are under significant suspicion it is probably sufficient to convert all suspicion levels into 'High' or 'Low'. If the system design provides tests which map cleanly onto the system organization, then the high and low suspicion levels will fall into groups matching units in the system representation.

Figure 14 displays sample probabilities which might exist at some step of diagnosis. The probabilities of higher levels of organization are simply the sums of their sub-element probabilities.

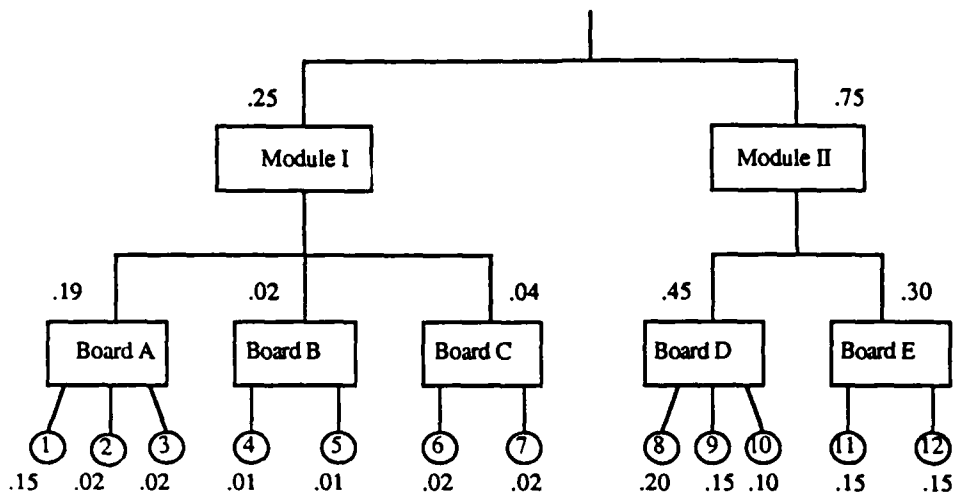


Figure 14. Current Suspicion Levels

From Figure 14, it is seen that all the components on boards D and E are suspected to a meaningful degree, as is one component in board A. A verbal characterization of the current suspicion state is "we suspect all components in module II, and component 1 in board A of module I." This characterization is made as concise as possible by grouping all significant suspicions as much as possible.

Figure 15 displays this characterization graphically. Note that sub-groups of system elements are combined into higher levels whenever their suspicion levels are similar. If some elements are suspected highly and others are not, then no further grouping is done.

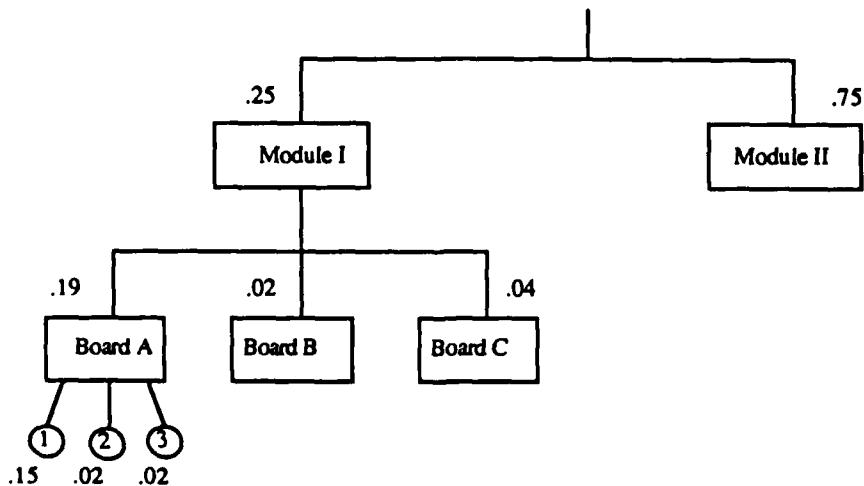


Figure 15. Suspicion Characterization

Now consider an alternative state of suspicions, as shown in Figure 16. This state might result from performing a different test than that performed to produce Figure 14. Here, all components in module II are suspected highly, and no component in module I is suspected highly. This state could be the result of a single test which monitors the entire functioning of one of the modules and is in no way affected by the other, or it could reflect the cumulative effects of a series of tests.

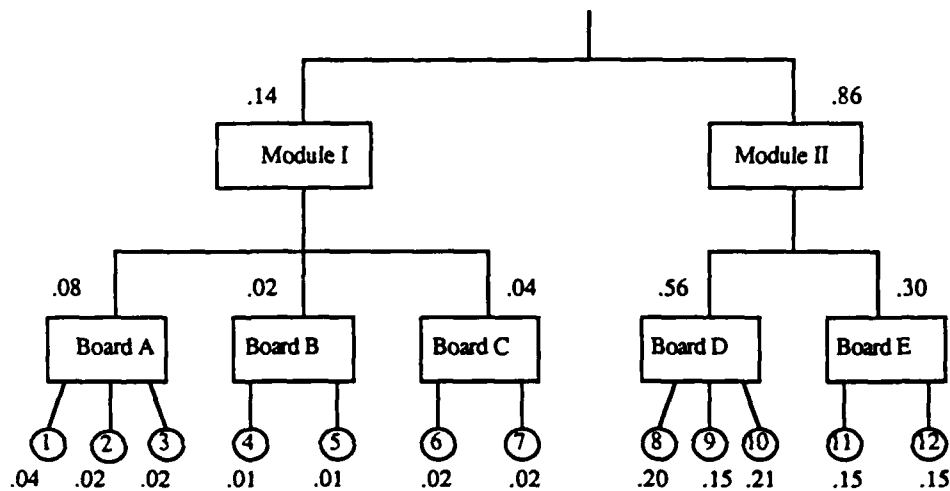


Figure 16. Suspicion Levels Resulting From an Alternative Test

The suspicions shown in Figure 16 may be stated as "we suspect everything in module II and nothing in module I." Figure 17 illustrates the suspicion situation graphically, after simplification.

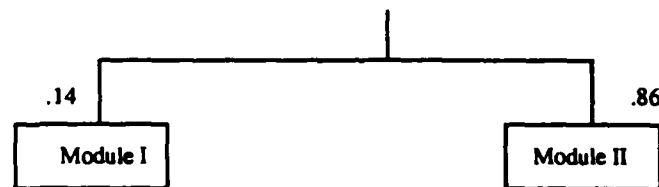


Figure 17. Simplified Suspicion State Following Alternative Test

Quantifying Complexity at a Stage. The following formula is used to quantify the complexity,  $C_p$ , of a suspicion state, in terms of the suspicion levels of the sub-elements at a stage

in a diagnostic sequence:

$$C_p = - \sum p_i \ln p_i$$

where  $C_p$  is the complexity of the suspicion state at the stage in the sequence

$p_i$  is the probability, or suspicion level, of the  $i$ th element at that stage

This classical expression for entropy yields higher values when many elements are suspected equally, and lower values when there are a few elements or when most of the uncertainty (suspicion) is centered upon a few elements. According to this expression, the complexity of the sample system shown in Figure 15 is as follows:

$$\begin{aligned} C_p &= - (.15 \ln .15 + .02 \ln .02 + .02 \ln .02 + .02 \ln .02 + .04 \ln .04 + .75 \ln .75) \\ &= - ( \quad -.28 \quad \quad -.08 \quad \quad -.08 \quad \quad -.08 \quad \quad -.13 \quad \quad -.22 ) \\ &= - (-0.87) \\ &= 0.87 \end{aligned}$$

whereas the complexity of the suspicion state shown in Figure 17 is

$$\begin{aligned} C_p &= - (.14 \ln .14 + .86 \ln .86) \\ &= - (-.28 - .13) \\ &= 0.41 \end{aligned}$$

In summary, the complexity of a suspicion state is determined by the following process:

1. determine a suspicion level for each replaceable unit (RU) in the system
2. recursively combine all elements which are suspected to a similar degree
3. compute the complexity of the resulting state, as  $C_p = -\sum p_i \ln p_i$

In general, the state complexity will be low at the beginning of a diagnostic sequence, for early tests tend to address high-level units of system hardware, and therefore low-level subcomponents are unlikely to be suspected to widely differing degrees. As testing proceeds, however, more specialized tests are performed, which monitor some of the low-level functions. When this occurs the suspicion state is likely to become far more complex. Late in a diagnostic sequence, the state complexity will usually return to a low level, for the suspicions are generally confined to a few low-level elements. If even a few such suspected elements reside in different system functions or hardware units, however, the complexity can be high until the fault is finally identified.

Computing Total Process Complexity. The total process complexity for a diagnosis sequence is computed as the sum of the state complexity values,  $C_p$ , following each test. Unlike operational complexity, the measure of process complexity is sensitive to the symptoms produced by a particular fault, and to the maintainability features of the system design. If a particular fault can be isolated easily, and with few tests, then the total process complexity will be low. Faults which force the troubleshooter to perform many tests, or tests which do not map well onto the current suspicion state, will yield higher values.

The measure of process complexity offers several advantages over more classical approaches to assessing the complexity of a system design, such as counting the number of signals and system elements. First, it is sensitive to the relationship between the system design and the maintainability features provided to monitor system functions. A system can be composed of an immense number of components, yet reflect ease of maintenance in the process complexity measure, if the tests available to the maintainer allow for easy partitioning of suspicion about the source of the fault. Some computers, for example, are constructed of a very high number of components, yet are relatively easy to maintain because the tests are easily performed and interpreted. A second advantage of the process complexity measure is that it can identify particular faults which involve relatively high diagnostic complexity. This affords the designer an opportunity to explore design revisions which could relieve the difficulties. Finally, a potential benefit of computing total process complexity from individual state complexities is that it may be found that cognitive workload is related more to the maximum complexity encountered within a problem than to the sum of the state values. Since all suspicion state values are available within PROFILE, it will be possible to retain both the maximum complexity level and the length of time the expert troubleshooter remained in each complexity state.

Two additional comments should be made about the procedure for computing process complexity. First, there are almost always alternative hierarchical representations of a system. A representation could reflect the physical packaging of the system, its functional relationships, or some hybrid combination of the two. Even when focusing on just one type, such as the functional hierarchy, two experts can differ in representing the system. The implication of this is that process complexity depends upon the representation of the system. If one individual views the system physically, as novices tend to do, then the complexity of that person's diagnosis strategy will be deeply affected by this conception. If experts conceive of a system in more functional terms, then the complexity follows this form. Most likely, experts have alternative representations which they employ depending upon the circumstances. Similarly, some system designs may encourage functional thinking, while others may be easily viewed with physical representations.

Secondly, it is recognized that the exact procedure for combining like-suspected elements has

not been specified in complete detail here. In the examples, suspicions were considered 'high' if the level exceeded about 0.10, and 'low' otherwise. Many other absolute and relative schemes are possible for combining elements into larger conceptual chunks, and some of these have been informally explored. Until more specialized studies are conducted, however, the best way to perform this step will remain unclear. The objective ought to be to determine what scheme produces suspicion representations most like those held by actual maintainers.

### Executive Complexity

Executive complexity relates to the significance of the options which must be weighed by the troubleshooter in managing fault diagnosis performance. In general, the time to decide upon a particular action will be affected by the gravity of the actions under consideration. The data support the notion that when the maintainer is about to perform a lengthy action, or one involving replacement of more expensive units of hardware, the cognitive decision time increases. This effect may also be true when the impending action is either dangerous, uncomfortable, or error-prone.

In some corrective maintenance settings the implications of alternatives is quite high. One test might involve a time-consuming and costly configuration of people and equipments, while another could involve an error-prone or dangerous disassembly which could create a need to perform a difficult re-calibration. In such a case the troubleshooter must weigh alternatives with significant implications, and would be expected to expend considerably more time considering the issues.

The interstep-cognitive time data described in section III provided a function relating cognitive time to the manual performance time of the impending action. What those data could not indicate was what portion of the time function was a result of the operational complexity of the particular system under test, what part was related to the complexity of the particular diagnostic process, and what part was influenced by the available choices. One hypothesis is that the intercept of the function is related in some manner to the operational complexity of the system under repair, the exponential form of the curve is related to the time significance of the alternatives, and the large variations about the mean time values for each sample point were due to variations in the process complexity which were not controlled.

Currently, PROFILE can detect decision points involving significant time implications, and it can recognize when a replacement of a costly spare part is about to be performed. It could also incorporate considerations of test danger or discomfort into its decision process, if test cost, currently expressed in time, were weighted by an appropriate factor reflecting the environment in which the test is performed. PROFILE cannot currently deal with the very real issue of human error, however.

## SECTION V. SUMMARY AND CONCLUSIONS

Fault diagnosis is regarded primarily as a cognitive activity supported by the performance of manual actions which are performed to obtain new information. This does not imply that the majority of time diagnosing a fault is purely cognitive. In three experimental studies conducted of fault diagnosis in electronic maintenance, the average time devoted to purely cognitive activity ranged from approximately one-third to one-half the total corrective maintenance time.

### Summary

The central objective of this investigation was to develop a generalized procedure for projecting cognitive time expended during fault diagnosis. The approach was to search for characteristics of experimentally observed diagnostic performance which were related to actual cognitive time expenditures, and then to project those characteristics and associated times for a particular system, and sample of faults, using PROFILE. Toward this end, a total of 638 fault diagnosis episodes were analyzed in detail. Guided by the findings of this analysis, three alternative approaches to projecting cognitive time were derived, one of which appears to be relatively reliable across system designs. This approach, which is a function of the manual times of the individual tests and the number of tests performed, has been implemented within PROFILE for use in projecting total corrective maintenance times.

A fundamentally different, and yet more ambitious, approach to projecting cognitive workload is to attempt to identify generic sources of cognitive difficulty which can be quantitatively evaluated for particular faults in particular system designs. This report has attempted to outline what those generic types of complexity might be, and how they may be quantified individually.

### Experimentally Observed Diagnostic Performance

In all three studies of diagnostic performance, cognitive time per fault diagnosed was significantly correlated to all of the following: 1) number of tests performed, 2) manual time expended in testing and 3) cognitive time per test.

An analysis of individual diagnostic performance showed that individuals who expended more cognitive time in fault diagnosis did not differ significantly from those who expended less cognitive time, in terms of the manual time spent testing and the number of tests performed.

Individuals who completed fault diagnosis in the least total time (manual plus cognitive), however, generally expended less cognitive time and less manual time, they performed fewer tests, and they expended less cognitive time per test, than diagnosticians requiring more total time.

Faults which required increased cognitive time to solution generally required more tests, and higher cognitive time per test, than faults involving a lower cognitive time workload.

### **Projecting Cognitive Time Workload**

The most promising characteristics of PROFILE diagnostic sequences, for the purpose of projecting cognitive time, were found to be 1) the manual times of the individual tests performed, and 2) the number of tests to diagnose a fault. When cognitive time is computed as a function of these two factors, the projections of cognitive time are relatively accurate.

### **Generic Complexity Types in Fault Diagnosis**

Three types of complexity are defined. These are considered to mutually influence the cognitive workload in fault diagnosis.

Operational complexity reflects the complexity of the system under repair, in general. Quantification of this characteristic is feasible in the relatively near future, if means can be developed for expressing system designs in terms of comparable simple functions and simple outputs.

Process complexity reflects the nature of the diagnostic sequence performed by an expert troubleshooter to identify a particular fault, and is computed by summing the complexity of the suspicion state at each stage of fault isolation. The suspicion state is formed by manipulating the system hierarchy such that it represents the major system elements suspected and not suspected, following each test. This technique identifies faults which involve complicated testing sequences and it is sensitive to aspects of the system design which complicate diagnosis.

Executive complexity has to do with the significance of the choices facing the troubleshooter. If the alternatives under consideration involve serious time, cost, or personal safety factors, then executive complexity increases, and, apparently so does the cognitive time involved in the decision. The data analyzed in this research provided one view of executive complexity, in the form of varying time costs of tests. The relationship between actual inter-step cognitive times and the manual times of the following tests indicates that cognitive time increases as the time of the test under consideration increases, but rapidly approaches an asymptote.

## Conclusions

This research represents a beginning in attempting to quantify cognitive workload in fault diagnosis. The retrospective analysis of experimentally obtained performance data reveals significant relationships, suggesting that expenditure of cognitive time is related to specific characteristics of the diagnostic context and content. The PROFILE model of expert troubleshooting strategy has provided a resource for quantifying those characteristics, and, with some adjusting for internal bias, has produced diagnostic routines whose characteristics correspond in meaningful ways with actual cognitive times.

Even very strong relationships among variables, however, do not satisfy the requirements for a projection technique until and unless the parameters of those relationship are validated for generality across a number of domains. The relationship between inter-step cognitive time and the manual time of the following test was examined in three relatively diverse experimental settings, and found to be quite similar across those domains. Further experimentation should be conducted 1) to test this relationship across a wider range of diagnostic environments, 2) to explore its generality at much higher time values, and 3) to determine what aspects of the relationship are affected by the design of the system, and the particular complexity of the diagnostic process at the time of performance.

This work was greatly facilitated by an unusually substantial body of actual troubleshooting performance data. Because of the relatively realistic environment in which these studies were conducted (i.e., the troubleshooters were not asked to explain their work, nor were they interrupted in any manner to facilitate data collection), the validity of the data is believed to be very high.

As would be expected, this experimental approach also had associated disadvantages. Since the original studies of diagnostic performance were not conducted for the primary purpose of exploring cognitive workload, a number of critical questions could not be examined. Interestingly, however, there are a number of examinations of the existing data which could yield more understanding, but remain to be performed. The most promising of these would be a study of the variations of inter-step cognitive times prior to tests of approximately the same time duration. It is suspected that these variations could be largely explained in terms of the particular process complexity that existed at each step.

The types of studies which should now be conducted to resolve many of the questions raised here are now much clearer as well. Of particular value would be the observation of a large number of carefully controlled decision tasks, including the following:

Cognitive time related to symptom assessment. The measure of interest is the time required to

judge the normality of a test result. Within a few systems, subjects would be given a sequence of test symptoms, and be asked to judge the normality of each reading.

Cognitive time related to symptom interpretation. The measure of interest is the time required to interpret a test result in terms of the possible sources. Subjects would be given test results, including whether those results are normal or abnormal, and be asked to interpret the significance of each reading.

Cognitive time related to test selection. Subjects would be given a suspicion state, i.e., a set of suspected elements in a system, and be asked to select the next test to perform.

All three of the above investigations would have to be done over a range of operational complexity and process complexity, quantified as outlined in section IV.

Cognitive time related to characteristics of alternatives. Subjects would be given a small set of alternative actions and associated expectations and costs, and be asked to choose a course of action.

Unfortunately, studies one and two, above, involve cognitive functions which we can only presume are performed, and both require the individual to perform some response for our benefit which may involve further cognitive functions or may alter the way the individual would naturally respond to the situation. It would be expected that the results of such studies would serve as a guide in then conducting more whole-task studies, similar to those used in this research, to explore cognitive workload in a realistic context. The three types of cognitive complexity developed here may serve as useful control variables.

The examination of complexity may also provide a somewhat broader or more precise outlook upon the objectives which should be sought to ease corrective maintenance. To the designer, a measure of complexity of diagnosis could have significance in evaluating alternative maintainability features, and someday the procurement of systems may include specifications concerning ease of maintenance in terms which could be so quantified.

To those concerned with maintenance procedures and maintenance training, a consideration of complexity could suggest that preferred approaches to fault isolation may not always be those which are most powerful, from the standpoint of amount of information obtained. For example, research might determine that fault isolation is more reliable and timely when the tests are selected to yield less than the maximum amount possible, at each stage, thereby easing the task of interpreting the results. Currently this is a question which is not formally raised, since there has been no workable means for assessing the values needed. As a result, maintainers are typically drilled to select the most powerful tests available. On the job, however, it may be that the

troubleshooters are relatively sensitive to judging what information would be meaningful to them, and what tests they can perform with a minimum of chance for error.

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# Appendix A - Individual Technician Performance Data

System	Technician Number	Average Manual Time	Average Cognitive Time	Average Number of Tests	Average Cognitive Time per Test	Average Number of Replacements
IR	1	347	230	13.7	16.8	1.6
IR	2	451	321	14.0	22.9	1.4
IR	3	375	253	19.8	12.8	1.5
IR	4	566	540	15.9	34.0	1.6
IR	5	241	363	24.2	15.0	3.4
IR	6	407	401	10.1	39.7	1.8
IR	7	501	358	21.1	17.0	3.3
IR	8	282	391	13.9	28.1	1.1
IR	9	282	476	12.8	37.2	1.6
IR	10	199	492	11.3	43.5	1.9
GN	1	253	133	3.3	40.3	2.6
GN	2	205	95	3.5	27.1	1.9
GN	3	265	126	3.3	38.2	2.1
GN	4	306	219	4.0	54.8	2.1
GN	5	221	100	3.4	29.4	2.0
GN	6	211	182	3.0	60.7	2.0
GN	7	265	145	1.3	111.5	2.3
GN	8	330	105	4.6	22.8	2.4
GN	9	348	109	4.4	24.8	1.7
GN	10	333	145	4.3	33.7	2.9
GN	11	250	170	3.7	45.9	1.7
GN	12	286	148	4.2	35.2	2.6
GN	13	218	93	3.9	23.8	1.9
GN	14	319	71	4.0	17.8	0.9
GN	15	292	142	3.6	39.4	1.0
GN	16	283	113	3.8	29.7	1.2
GN	17	363	176	2.5	70.4	1.9
GN	18	258	108	3.9	27.7	1.5
GN	19	246	151	2.9	52.1	2.0
GN	20	267	162	3.7	43.8	2.8
GN	21	324	186	3.6	51.7	2.3
GN	22	283	174	3.5	49.7	2.9
GN	23	347	119	3.9	30.5	2.0
GN	24	178	115	2.8	41.1	1.1
GN	25	316	164	3.4	48.2	2.1
GN	26	223	91	3.0	30.3	2.1
GN	27	228	108	2.9	37.2	1.6
GN	28	261	125	3.5	35.7	1.4
GN	29	222	154	3.1	49.7	2.0

IR - Infrared Transmitter/Receiver System  
GN - Graphics Network System  
MC - Microcomputer System

# Appendix A - Individual Technician Performance Data

MC	1	666	203	7.4	27.4	2.4
MC	2	648	212	7.3	29.0	1.6
MC	3	527	320	6.6	48.5	2.0
MC	4	592	453	7.1	63.8	2.0
MC	5	558	359	6.8	52.8	1.6
MC	6	685	208	7.7	27.0	1.7
MC	7	602	200	6.3	31.7	1.8
MC	8	766	290	7.9	36.7	2.0
MC	9	686	300	7.4	40.5	2.4
MC	10	381	267	4.6	58.0	1.8
MC	11	553	254	6.9	36.8	1.5
MC	12	421	185	5.4	34.3	1.6
MC	13	528	272	6.9	39.4	1.9
MC	14	617	370	7.0	52.9	1.6
MC	15	560	255	6.8	37.5	1.8
MC	16	630	210	7.0	30.0	1.8
MC	17	549	190	6.7	28.4	1.8
MC	18	564	186	6.6	28.2	2.0
MC	19	588	354	6.8	52.1	1.2
MC	20	612	439	6.6	66.5	3.2
MC	21	521	185	6.7	27.6	1.6
MC	22	541	363	7.0	51.9	1.9
MC	23	471	165	5.0	33.0	1.2
MC	24	510	251	6.1	41.1	2.0
MC	25	564	288	6.6	43.6	1.5
MC	26	674	161	6.9	23.3	1.9
MC	27	660	277	7.1	39.0	1.8
MC	28	571	306	6.6	46.4	1.6
MC	29	665	353	8.9	39.7	2.1
MC	30	563	278	6.4	43.4	1.8
MC	31	572	357	6.6	54.1	1.6
MC	32	614	317	7.1	44.6	1.9
MC	33	568	200	6.4	31.3	1.8
MC	34	578	306	7.6	40.3	2.2
MC	35	583	230	6.4	35.9	2.2
MC	36	643	434	6.8	63.8	3.0
MC	37	347	226	4.2	53.8	1.4
MC	38	531	182	5.5	33.1	1.6
MC	39	695	256	7.5	34.1	1.9
MC	40	788	259	8.7	29.8	2.5
MC	41	472	276	6.4	43.1	1.4
MC	42	577	296	7.2	41.1	2.0
MC	43	721	299	7.6	39.3	2.0
MC	44	500	261	5.9	44.2	1.6
MC	45	489	223	6.6	33.8	1.6
MC	46	599	115	6.8	16.9	2.1
MC	47	397	214	5.4	39.6	2.2
MC	48	488	136	5.8	23.4	1.6

# Appendix B - Problem Data

Problem	Manual Time	Cognitive Time	Number Tests	Number Replacements
IR1	692	687	24.0	1.5
IR2	307	223	15.0	2.8
IR3	335	317	22.0	4.0
IR4	448	467	15.8	2.2
IR5	334	310	10.8	1.2
IR6	602	983	23.4	3.0
IR7	217	242	13.4	1.0
IR8	170	91	7.2	1.0
IR9	564	653	21.2	2.8
IR10	242	262	9.8	1.2
IR11	367	291	12.6	1.0
IR12	415	504	14.3	1.0
IR13	190	270	11.2	1.2
IR14	546	376	18.4	2.2
IR15	111	147	9.6	1.6
IR16	293	304	14.2	1.6
MC1	442	251	5.3	1.7
MC2	249	139	4.7	1.2
MC3	845	294	7.7	2.7
MC4	793	252	9.3	2.0
MC5	623	217	7.8	2.4
MC6	621	260	6.1	1.9
MC7	318	117	4.8	1.2
MC8	715	323	7.9	1.8
GN1	183	129	4.9	2.8
GN2	124	95	3.9	1.8
GN3	286	150	3.3	3.1
GN4	303	178	5.5	3.5
GN5	161	109	6.0	2.1
GN6	341	151	5.1	2.4

IR - Infrared Transmitter/Receiver System  
GN - Graphics Network System  
MC - Microcomputer System

# Appendix C -Performance Data by Technician Group

Students ranked into thirds, based upon Cognitive time per problem					
IR System	Manual	Cognitive	Tests	Cog/test	N
Lower	391	268	15.8	17.0	3
Middle	358	378	17.3	21.9	4
Higher	349	503	13.3	37.8	3
Graphics Network					
Lower	263	99	3.7	26.8	10
Middle	276	133	3.4	39.1	9
Higher	279	174	3.3	52.7	10
Microcomputer					
Lower	563	185	6.4	28.9	16
Middle	560	260	6.6	39.4	16
Higher	604	352	7.1	49.6	16
Students ranked into thirds, based upon Total time per problem					
IR System	Manual	Cognitive	Tests	Cog/test	N
Lower	321	282	19.2	14.7	3
Middle	304	420	13.5	31.1	4
Higher	491	433	15.7	27.6	3
Graphics Network					
Lower	227	112	3.3	33.9	10
Middle	266	141	3.3	42.7	9
Higher	324	154	3.8	40.5	10
Microcomputer					
Lower	488	204	5.9	34.6	16
Middle	594	250	6.9	36.2	16
Higher	645	343	7.3	47.0	16

Appendix D - Detailed PROFILE Projections

PROFILE PROJECTIONS						
Problem	Test No.	Test Time	Occ.'s	Manual Time	Cog. Time	Total Time
IR1	1	10	1.0	10.0	14.5	24.5
	60	2	1.0	2.0	11.6	13.6
	59	23	1.0	23.0	17.7	40.7
	1	10	1.0	10.0	14.5	24.5
	7	48	1.0	48.0	22.4	70.4
	58	49	1.0	49.0	22.5	71.5
	1	10	1.0	10.0	14.5	24.5
	26	55	1.0	55.0	23.5	78.5
	29	43	1.0	43.0	21.5	64.5
	35	55	1.0	55.0	23.5	78.5
	43	24	1.0	24.0	17.9	41.9
	42	66	1.0	66.0	25.2	91.2
	40	38	1.0	38.0	20.6	58.6
	37	48	1.0	48.0	22.4	70.4
	38	48	1.0	48.0	22.4	70.4
	R36	35	1.0	35.0	20.1	55.1
	1	10	1.0	10.0	14.5	24.5
	TOTAL=			574.0	329.2	903.2
IR2	1	10	1.0	10.0	14.5	24.5
	60	2	1.0	2.0	11.6	13.6
	59	23	1.0	23.0	17.7	40.7
	60	8	1.0	8.0	13.9	21.9
	15	60	1.0	60.0	24.3	84.3
	13	30	1.0	30.0	19.1	49.1
	14	28	1.0	28.0	18.7	46.7
	52	58	1.0	58.0	24.0	82.0
	49	28	1.0	28.0	18.7	46.7
	R10	27	1.0	27.0	18.5	45.5
	60	2	1.0	2.0	11.6	13.6
	TOTAL=			276.0	192.6	468.6
IR3	1	10	1.0	10.0	14.5	24.5
	60	2	1.0	2.0	11.6	13.6
	59	23	1.0	23.0	17.7	40.7
	60	8	1.0	8.0	13.9	21.9
	15	60	1.0	60.0	24.3	84.3
	16	35	1.0	35.0	20.1	55.1
	54	55	1.0	55.0	23.5	78.5
	R17	8	0.4	3.2	5.5	8.7
	60	2	0.4	0.8	4.6	5.4
	R14	27	1.0	27.0	18.5	45.5
	60	2	1.0	2.0	11.6	13.6
	TOTAL=			226.0	165.8	391.8

Note: When PROFILE must select an element for replacement among two or more which are equally expensive and equally suspected, it selects the order of replacement randomly. This appendix lists those replacements in numerical order, along with their respective frequency of replacement (see problem IR 4, for example).

# Appendix D - Detailed PROFILE Projections

IR4	1	10	1.0	10.0	14.5	24.5
	60	2	1.0	2.0	11.6	13.6
	59	23	1.0	23.0	17.7	40.7
	1	10	1.0	10.0	14.5	24.5
	7	48	1.0	48.0	22.4	70.4
	58	49	1.0	49.0	22.5	71.5
	1	10	1.0	10.0	14.5	24.5
	26	55	1.0	55.0	23.5	78.5
	29	43	1.0	43.0	21.5	64.5
	25	50	1.0	50.0	22.7	72.7
	23	49	1.0	49.0	22.5	71.5
R23		27	0.4	10.8	7.4	18.2
	1	10	0.4	4.0	5.8	9.8
R24		27	0.4	10.8	7.4	18.2
	1	10	0.4	4.0	5.8	9.8
R25		27	0.2	5.4	3.7	9.1
	1	10	0.2	2.0	2.9	4.9
R26		27	0.2	5.4	3.7	9.1
	1	10	0.2	2.0	2.9	4.9
R27		27	1.0	27.0	18.5	45.5
	1	10	1.0	10.0	14.5	24.5
TOTAL				430.4	280.5	710.9
IR5	1	10	1.0	10.0	14.5	24.5
	37	87	1.0	87.0	28.2	115.2
	38	48	1.0	48.0	22.4	70.4
	58	49	1.0	49.0	22.5	71.5
	1	10	1.0	10.0	14.5	24.5
R20		27	1.0	27.0	18.5	45.5
	1	10	1.0	10.0	14.5	24.5
TOTAL				241	135.077	376.1
IR6	1	10	1.0	10.0	14.5	24.5
	60	2	1.0	2.0	11.6	13.6
	59	23	1.0	23.0	17.7	40.7
	1	10	1.0	10.0	14.5	24.5
	7	48	1.0	48.0	22.4	70.4
	58	49	1.0	49.0	22.5	71.5
	1	10	1.0	10.0	14.5	24.5
	26	55	1.0	55.0	23.5	78.5
	29	43	1.0	43.0	21.5	64.5
	25	50	1.0	50.0	22.7	72.7
	23	49	1.0	49.0	22.5	71.5
R25		27	1.0	27.0	18.5	45.5
	1	10	1.0	10.0	14.5	24.5
R26		27	0.2	5.4	3.7	9.1
	1	10	0.2	2.0	2.9	4.9
R27		27	0.6	16.2	11.1	27.3
	1	10	0.6	6.0	8.7	14.7
TOTAL				415.6	267.3	682.9

Appendix D - Detailed PROFILE Projections

IR7	1	10	1.0	10.0	14.5	24.5
	60	2	1.0	2.0	11.6	13.6
	59	23	1.0	23.0	17.7	40.7
	60	8	1.0	8.0	13.9	21.9
	8	29	1.0	29.0	18.9	47.9
R32		27	1.0	27.0	18.5	45.5
	1	10	1.0	10.0	14.5	24.5
TOTAL=				109.0	109.5	218.5
IR8	1	10	1.0	10.0	14.5	24.5
	60	2	1.0	2.0	11.6	13.6
	59	23	1.0	23.0	17.7	40.7
	60	8	1.0	8.0	13.9	21.9
	15	60	1.0	60.0	24.3	84.3
	16	35	1.0	35.0	20.1	55.1
	54	55	1.0	55.0	23.5	78.5
R17		8	1.0	8.0	13.9	21.9
	1	10	1.0	10.0	14.5	24.5
TOTAL=				211.0	153.8	364.8
IR9	1	10	1.0	10.0	14.5	24.5
	7	48	1.0	48.0	22.4	70.4
	15	55	1.0	55.0	23.5	78.5
	19	43	1.0	43.0	21.5	64.5
	29	65	1.0	65.0	25.1	90.1
	37	82	1.0	82.0	27.5	109.5
	43	12	1.0	12.0	15.0	27.0
	40	55	1.0	55.0	23.5	78.5
	41	38	1.0	38.0	20.6	58.6
	38	48	1.0	48.0	22.4	70.4
R36		35	1.0	35.0	20.1	55.1
	1	10	1.0	10.0	14.5	24.5
TOTAL=				501.0	250.7	751.7
IR10	1	10	1.0	10.0	14.5	24.5
	7	48	1.0	48.0	22.4	70.4
	15	55	1.0	55.0	23.5	78.5
	36	24	1.0	24.0	17.9	41.9
	13	35	1.0	35.0	20.1	55.1
	14	28	1.0	28.0	18.7	46.7
	16	42	1.0	42.0	21.4	63.4
R35		35	0.8	28.0	16.1	44.1
	1	10	0.8	8.0	11.6	19.6
R10		27	1.0	27.0	18.5	45.5
	1	10	1.0	10.0	14.5	24.5
TOTAL=				315.0	199.1	514.1

Appendix D - Detailed PROFILE Projections

IR11	1	10	1.0	10.0	14.5	24.5
	7	48	1.0	48.0	22.4	70.4
	15	55	1.0	55.0	23.5	78.5
	19	43	1.0	43.0	21.5	64.5
	16	40	1.0	40.0	21.0	61.0
R17	8	8	1.0	8.0	13.9	21.9
	1	4	1.0	4.0	12.5	16.5
R14	27	27	1.0	27.0	18.5	45.5
	1	10	1.0	10.0	14.5	24.5
TOTAL=				245.0	162.2	407.2
IR12	1	10	1.0	10.0	14.5	24.5
	7	48	1.0	48.0	22.4	70.4
	15	55	1.0	55.0	23.5	78.5
	19	43	1.0	43.0	21.5	64.5
	29	65	1.0	65.0	25.1	90.1
	26	28	1.0	28.0	18.7	46.7
	23	60	1.0	60.0	24.3	84.3
	24	38	1.0	38.0	20.6	58.6
	25	44	1.0	44.0	21.7	65.7
R24	27	27	0.6	16.2	11.1	27.3
	1	10	0.6	6.0	8.7	14.7
R25	27	27	0.2	5.4	3.7	9.1
	1	10	0.2	2.0	2.9	4.9
R26	27	27	0.2	5.4	3.7	9.1
	1	10	0.2	2.0	2.9	4.9
R27	27	27	1.0	27.0	18.5	45.5
	1	10	1.0	10.0	14.5	24.5
TOTAL=				465.0	258.3	723.3
IR13	1	10	1.0	10.0	14.5	24.5
	37	87	1.0	87.0	28.2	115.2
	38	48	1.0	48.0	22.4	70.4
R20	27	27	1.0	27.0	18.5	45.5
	1	10	1.0	10.0	14.5	24.5
TOTAL=				182.0	98.1	280.1

Appendix D - Detailed PROFILE Projections

IR14	1	10	1.0	10.0	14.5	24.5
	7	48	1.0	48.0	22.4	70.4
	15	55	1.0	55.0	23.5	78.5
	19	43	1.0	43.0	21.5	64.5
	29	65	1.0	65.0	25.1	90.1
	26	28	1.0	28.0	18.7	46.7
	23	60	1.0	60.0	24.3	84.3
	24	38	1.0	38.0	20.6	58.6
	25	44	1.0	44.0	21.7	65.7
R23		27	0.2	5.4	3.7	9.1
	1	10	0.2	2.0	2.9	4.9
R24		27	0.4	10.8	7.4	18.2
	1	10	0.4	4.0	5.8	9.8
R25		27	1.0	27.0	18.5	45.5
	1	10	1.0	10.0	14.5	24.5
R26		27	0.8	21.6	14.8	36.4
	1	10	0.8	8.0	11.6	19.6
R27		27	0.4	10.8	7.4	18.2
	1	10	0.4	4.0	5.8	9.8
TOTAL=				494.6	284.7	779.3
IR15	1	10	1.0	10.0	14.5	24.5
	7	48	1.0	48.0	22.4	70.4
	8	19	1.0	19.0	16.8	35.8
R32		27	1.0	27.0	18.5	45.5
	1	10	1.0	10.0	14.5	24.5
TOTAL=				114.0	86.6	200.6
IR16	1	10	1.0	10.0	14.5	24.5
	7	48	1.0	48.0	22.4	70.4
	15	55	1.0	55.0	23.5	78.5
	19	43	1.0	43.0	21.5	64.5
	16	40	1.0	40.0	21.0	61.0
R14		27	0.4	10.8	7.4	18.2
	1	10	0.4	4.0	5.8	9.8
R17		8	1.0	8.0	13.9	21.9
	1	10	1.0	10.0	14.5	24.5
R35		35	0.2	7.0	4.0	11.0
	1	10	0.2	2.0	2.9	4.9
TOTAL=				237.8	151.3	389.1

# Appendix D - Detailed PROFILE Projections

MC1	5	29	1.0	29.0	18.9	47.9
	7	57	1.0	57.0	23.8	80.8
	R1	196	1.0	196.0	40.9	236.9
	5	29	1.0	29.0	18.9	47.9
	TOTAL=			311.0	102.6	413.6
MC2	5	29	1.0	29.0	18.9	47.9
	7	57	1.0	57.0	23.8	80.8
	R2	43	1.0	43.0	21.5	64.5
	5	29	1.0	29.0	18.9	47.9
	TOTAL=			158.0	83.2	241.2
MC3	5	29	1.0	29.0	18.9	47.9
	6	65	1.0	65.0	25.1	90.1
	10	57	1.0	57.0	23.8	80.8
	9	88	1.0	88.0	28.4	116.4
	3	78	1.0	78.0	27.0	105.0
	2	301	1.0	301.0	50.8	351.8
	R4	37	1.0	37.0	20.5	57.5
	2	301	1.0	301.0	50.8	351.8
	TOTAL=			956.0	245.3	1201.3
MC4	5	29	1.0	29.0	18.9	47.9
	7	57	1.0	57.0	23.8	80.8
	R9	55	1.0	55.0	23.5	78.5
	5	29	1.0	29.0	18.9	47.9
	8	109	1.0	109.0	31.1	140.1
	4	54	1.0	54.0	23.4	77.4
	14	57	1.0	57.0	23.8	80.8
	R7	85	1.0	85.0	28.0	113.0
	5	29	1.0	29.0	18.9	47.9
	15	24	1.0	24.0	17.9	41.9
	R19	14	1.0	14.0	15.6	29.6
	5	29	1.0	29.0	18.9	47.9
	R8	166	0.8	132.8	30.2	163.0
	5	29	0.8	23.2	15.1	38.3
	R6	98	1.0	98.0	29.7	127.7
	5	29	1.0	29.0	18.9	47.9
	TOTAL=			854.0	356.7	1210.7

Appendix D - Detailed PROFILE Projections

MC5	5	29	1.0	29.0	18.9	47.9
	7	57	1.0	57.0	23.8	80.8
	R9	55	1.0	55.0	23.5	78.5
	5	29	1.0	29.0	18.9	47.9
	8	109	1.0	109.0	31.1	140.1
	4	54	1.0	54.0	23.4	77.4
	14	57	1.0	57.0	23.8	80.8
	R7	85	1.0	85.0	28.0	113.0
	5	29	1.0	29.0	18.9	47.9
	TOTAL=			504.0	210.4	714.4
MC6	5	29	1.0	29.0	18.9	47.9
	7	57	1.0	57.0	23.8	80.8
	R9	55	1.0	55.0	23.5	78.5
	5	29	1.0	29.0	18.9	47.9
	8	109	1.0	109.0	31.1	140.1
	4	54	1.0	54.0	23.4	77.4
	14	57	1.0	57.0	23.8	80.8
	R7	85	1.0	85.0	28.0	113.0
	5	29	1.0	29.0	18.9	47.9
	15	24	1.0	24.0	17.9	41.9
	R8	166	1.0	166.0	37.7	203.7
	5	29	1.0	29.0	18.9	47.9
	TOTAL=			723.0	285.0	1008.0
MC7	5	29	1.0	29.0	18.9	47.9
	6	65	1.0	65.0	25.1	90.1
	10	57	1.0	57.0	23.8	80.8
	R13	23	1.0	23.0	17.7	40.7
	5	29	1.0	29.0	18.9	47.9
	TOTAL=			203.0	104.4	307.4
MC8	5	29	1.0	29.0	18.9	47.9
	4	54	1.0	54.0	23.4	77.4
	R9	55	1.0	55.0	23.5	78.5
	5	29	1.0	29.0	18.9	47.9
	14	57	1.0	57.0	23.8	80.8
	R7	85	1.0	85.0	28.0	113.0
	5	29	1.0	29.0	18.9	47.9
	R8	166	0.4	66.4	15.1	81.5
	5	29	0.4	11.6	7.6	19.2
	R19	14	1.0	14.0	15.6	29.6
	5	29	1.0	29.0	18.9	47.9
	TOTAL=			459.0	212.6	671.6

# Appendix D - Detailed PROFILE Projections

GN1	1	5	1.0	5.0	12.8	17.8
	3	10	1.0	10.0	14.5	24.5
	4	15	1.0	15.0	15.8	30.8
R17		15	1.0	15.0	15.8	30.8
	1	5	1.0	5.0	12.8	17.8
	5	20	1.0	20.0	17.0	37.0
R7		60	1.0	60.0	24.3	84.3
	1	5	1.0	5.0	12.8	17.8
TOTAL				135.0	126.0	261.0
GN2	1	5	1.0	5.0	12.8	17.8
	3	10	1.0	10.0	14.5	24.5
	12	30	1.0	30.0	19.1	49.1
R16		30	1.0	30.0	19.1	49.1
	1	5	1.0	5.0	12.8	17.8
TOTAL				80.0	78.4	158.4
GN3	1	20	1.0	20.0	17.0	37.0
	2	160	1.0	160.0	37.1	197.1
R4		40	1.0	40.0	21.0	61.0
	1	20	1.0	20.0	17.0	37.0
TOTAL				240.0	92.1	332.1
GN4	1	20	1.0	20.0	17.0	37.0
	3	40	1.0	40.0	21.0	61.0
R17		15	1.0	15.0	15.8	30.8
	1	20	1.0	20.0	17.0	37.0
R6		15	1.0	15.0	15.8	30.8
	1	20	1.0	20.0	17.0	37.0
	4	60	1.0	60.0	24.3	84.3
R8		35	0.8	28.0	16.1	44.1
	1	20	0.8	16.0	13.6	29.6
R9		60	0.2	12.0	4.9	16.9
	1	20	0.2	4.0	3.4	7.4
R5		35	1.0	35.0	20.1	55.1
	1	20	1.0	20.0	17.0	37.0
TOTAL				305.0	203.0	508.0
GN5	1	20	1.0	20.0	17.0	37.0
	8	20	1.0	20.0	17.0	37.0
	3	20	1.0	20.0	17.0	37.0
	2	20	1.0	20.0	17.0	37.0
	4	20	1.0	20.0	17.0	37.0
R3		50	1.0	50.0	22.7	72.7
	1	20	1.0	20.0	17.0	37.0
TOTAL				170.0	124.8	294.8

# Appendix D - Detailed PROFILE Projections

GN6	1	80	1.0	80.0	27.3	107.3
	8	80	1.0	80.0	27.3	107.3
	R17	15	1.0	15.0	15.8	30.8
	R15	20	1.0	20.0	17.0	37.0
	R14	30	1.0	30.0	19.1	49.1
	R16	30	1.0	30.0	19.1	49.1
	R8	35	1.0	35.0	20.1	55.1
	R3	50	1.0	50.0	22.7	72.7
	1	80	1.0	80.0	27.3	107.3
	TOTAL=			420.0	195.6	615.6

### ACTUAL AND PROJECTED PERFORMANCE DATA

ACTUAL PERFORMANCE DATA				PROFILE PROJECTIONS						
Problem	Manual		Cognitive	Total	Number		Replacements			
	Time	Time			Tests	Replacements				
IR1	692	687	1379	24.0	1.5	574	329	903	16.0	1.0
IR2	307	223	530	15.0	2.8	276	193	469	10.0	1.0
IR3	335	317	652	22.0	4.0	226	166	392	8.4	1.4
IR4	448	467	915	15.8	2.2	430	280	710	13.2	2.2
IR5	334	310	644	10.8	1.2	241	135	376	6.0	1.0
IR6	602	983	1585	23.4	3.0	416	267	683	12.8	1.8
IR7	217	242	459	13.4	1.0	109	110	219	6.0	1.0
IR8	170	91	261	7.2	1.0	211	154	365	8.0	1.0
IR9	564	653	1217	21.2	2.8	501	251	752	11.0	1.0
IR10	242	262	504	9.8	1.2	315	199	514	8.8	1.8
IR11	367	291	658	12.6	1.0	245	162	407	7.0	2.0
IR12	415	504	919	14.3	1.0	465	258	723	11.0	2.0
IR13	190	270	460	11.2	1.2	182	98	280	4.0	1.0
IR14	546	376	922	18.4	2.2	495	285	780	11.8	2.8
IR15	111	147	258	9.6	1.6	114	87	201	4.0	1.0
IR16	293	304	597	14.2	1.6	238	151	389	6.6	1.6
MC1	442	251	693	5.3	1.7	311	103	414	3.0	1.0
MC2	249	139	388	4.7	1.2	158	83	241	3.0	1.0
MC3	845	294	1139	7.7	2.7	956	245	1201	7.0	1.0
MC4	793	252	1045	9.3	2.0	854	357	1211	10.8	4.8
MC5	623	217	840	7.8	2.4	504	210	714	6.0	2.0
MC6	621	260	881	6.1	1.9	723	285	1008	9.0	3.0
MC7	318	117	435	4.8	1.2	203	104	307	4.0	1.0
MC8	715	323	1038	7.9	1.8	459	213	672	6.4	3.4
GN1	183	129	312	4.9	2.8	135	126	261	6.0	2.0
GN2	124	95	219	3.9	1.8	80	78	158	4.0	1.0
GN3	286	150	436	3.3	3.1	240	92	332	3.0	1.0
GN4	303	178	481	5.5	3.5	305	203	508	7.0	4.0
GN5	161	109	270	6.0	2.1	170	125	295	6.0	1.0
GN6	341	151	492	5.1	2.4	420	196	616	3.0	6.0

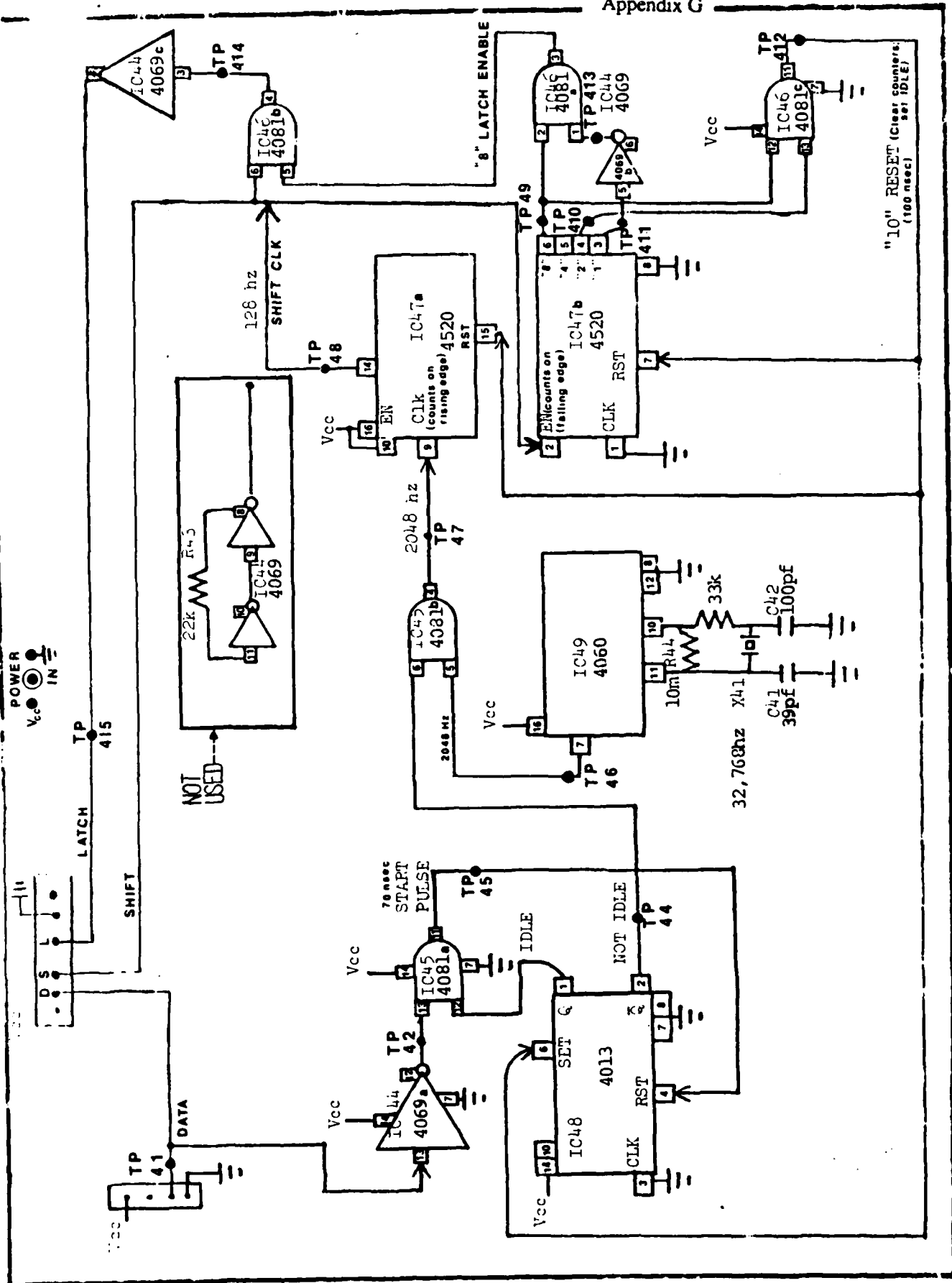
# Appendix F - Interstep Cognitive Time Summary

## COGNITIVE TIMES PRIOR TO TESTS:

Range of Test Times (sec.)	Category Mid-point	Total Actual Cognitive Time	Sample Size	Ave. Cog. Time (sec.)	Computed Cog. Time
3 to 7	5	830	86	9.7	12.8
8 to 14	10	2071	132	15.7	14.5
15 to 25	20	2131	143	14.9	17.0
26 to 35	30	2226	107	20.8	19.1
36 to 45	40	2107	98	21.5	21.0
46 to 65	55	2294	90	25.5	23.5
66 to 100	85	1856	66	28.1	28.0
101 to 200	150	1419	39	36.4	36.0

## COGNITIVE TIMES PRIOR TO REPLACEMENTS:

Range of Rplmt Times (sec.)	Category Mid-Point	Total Actual Cognitive Time	Sample Size	Ave. Cog. Time (sec.)	Computed Cog. Time
5 to 15	10	2684	110	24.4	18.0
16 to 25	20	375	25	15.0	15.8
26 to 35	30	1290	63	20.5	17.1
36 to 45	40	817	33	24.8	18.1
46 to 55	50	548	10	54.8	23.5
56 to 107	80	898	23	39.0	20.8



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